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Which Type of Sunlight is the Best Disinfectant? The Effectiveness of Information Disclosure Programs

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Title: Which Type of Sunlight is the Best Disinfectant? The Effectiveness of Information Disclosure Programs

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Abstract:

This study assesses the effectiveness of two information disclosure programs – the success of state-based mandatory carbon reporting programs and the voluntary Carbon Disclosure Project, which uses investor pressure to push firms to disclose carbon emissions and carbon management strategies. I match firms in each program to control groups of firms that have not participated in each program. Using panel data methods including a difference in differences model and fixed effects model, I measure the impact of each program on plant-level carbon emissions and plant-level carbon intensity. I find that the Carbon Disclosure Project is associated with reductions in plant level carbon intensity. State reporting programs do not have an impact on carbon intensity. Neither program impacted total carbon emissions. I conclude that participation in the CDP reflects changes made by firm managers that lead to improved carbon management.

Keywords: Voluntary Environmental Policy, Information Disclosure Programs, Climate Change Policy, Carbon Disclosure Project

JEL codes: Q50, Q54, Q58, D80, C23,

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1. Introduction

The use of information disclosure programs has been increasingly prevalent in order to improve risk management and allow for more cost-effective private-market and legal forces to replace the heavy hand of government intervention. A variety of examples include lead paint disclosures, toxic emissions data, drinking water quality notices, eco-label notices, health, hygiene, and nutrition labeling, surgeon general's warnings, and financial market data provision. Agricultural products increasingly are labeled with information regarding the origin or the product and organic labeling. Colleges, universities, and hospitals must disclose a variety of statistics and performance metrics. Increasingly, information provision and product labeling has come to represent a common way of attempting to provide consumers and investors with greater choice, without directly mandating behavioral changes from regulatory targets.

As industrialized nations prepare to deal with climate change policy, it has become increasingly important that quality greenhouse gas emissions data are collected from firms. The aggregation of this information is the first step towards improved management of greenhouse gases. In addition, the transparency of firm operations and the reduction of information asymmetry between firms and their investors and consumers may provide a vehicle for free-market environmental policy and the impetus for improved management and increased efficiency of greenhouse gas operations.

A variety of information disclosure programs have arisen on the national, state, and international levels. Since 1993, Wisconsin has mandated greenhouse gas emissions disclosure from large emitters of carbon dioxide (EPA 2009). Over time, the number of states requiring this disclosure has increased to 18 states, and as of January 1, 2010, a rule exists to require national greenhouse gas reporting from all large emitters. Additionally, the U.S. Securities and Exchange

Commission requires the disclosure of climate change related risks, as of February 10, 2010.

Voluntary initiatives have proliferated as well. The Department of Energy's 1605b program encourages firms to voluntarily report carbon emissions to the federal government. The Carbon Disclosure Project (CDP) is a private, non-profit voluntary initiative designed to improve transparency between firms and investors, and encourage improved management of greenhouse gases by firms.

Despite the proliferation of information disclosure programs and studies evaluating information disclosure programs, significant debate exists regarding the effectiveness of individual programs and more importantly, the comparative effectiveness of different approaches to information disclosure programs. Because research regarding information disclosure programs has demonstrated mixed results, increased attention has turned towards determining what makes some information disclosure programs more effective than others, or what makes information disclosure programs effective in some circumstances (Bae et al. 2010). Information disclosure programs can collect different types of information, use a variety of tools to disseminate information, and can be sponsored by government, industry groups, or non-governmental organizations (Darnall et al. 2009). As industrialized countries seek to address greenhouse gases, they are faced with an increasingly broad array of policy tools and approaches to policy that can be used to improve the governance of greenhouse gases, and evaluating policy experiments and institutional arrangements can lead to an improved understanding of institutional design and how to solve collective action problems (Ostrom 2005).

Using a panel of plant-level data, this research seeks to evaluate a private voluntary (the CDP) and a public mandatory approach (State Reporting Requirements) to the disclosure of carbon dioxide emissions. This research will help contribute to the debate regarding the effectiveness of information disclosure programs, while helping to shed light on the possible

tradeoffs between various designs of information disclosure approaches. The broader implications of this research may help policy-makers and researchers better understand the tradeoffs of voluntary and mandatory environmental policy, and an understanding of the extent to which information disclosure programs can play a role in the mix of policy tools used to address climate change. With the U.S. implementing mandatory greenhouse gas reporting and other greenhouse gas regulation, it is important to understand the expected impacts and tradeoffs of these policy approaches.

This research seeks to make contributions in three areas that are described in detail in the following sections. First, this research seeks to examine the difference across information disclosure programs that employ different program designs yet both target CO₂, in order to learn how to improve the effectiveness of information disclosure programs. Second, this research seeks to provide insight regarding the effectiveness of information disclosure programs on carbon dioxide and electricity generation, which may have different incentives and institutional arrangements than programs to address toxics or other environmental pollutants. Third, this research uses state-of-the-art statistical techniques in order to assess the effectiveness of a voluntary information disclosure program.

This research proceeds as follows: First, I discuss theory and evidence of the success of information disclosure programs in the realm of policy tools to address environmental problems. Second, I discuss the role of information disclosure programs as a type of voluntary environmental program and their role for addressing environmental problems. Third, I present theory and hypotheses related to the effectiveness of two information disclosure programs. Fourth, I discuss my research design, sample and methodology. I then present results and conclude with a discussion and conclusion, highlighting the implications of this research for climate change policy and environmental policy-making.

2. Literature and background of Information Disclosure

2.1. Theory regarding the success of information disclosure programs

Information disclosure programs can be run by government, as a mandatory or voluntary reporting program, but are increasingly designed as a form of ‘civil regulation’ (Murphy and Bendell 1999), where civil society actors pressure firms (rather than governments) to establish and adhere to environmental and social norms and standards. The institutionalization and standardization of information disclosure allows stakeholders to demand accountability and certain performance levels, rewarding strong performers and exerting pressure on poor performers or non-disclosers (Fiorino 2006). Information disclosure programs evolved as a response to the challenges of implementing increasingly expensive command and control regulatory policy (Bae et al. 2010). Traditional command and control policy has been associated with high costs and significant conflict between government, industry, and environmental groups (Portney and Stavins 2000). Regulatory innovation, including a move to market based mechanisms, voluntary programs, and information disclosure programs were thought of as ways to improve environmental outcomes using less costly and coercive policy tools (Konar and Cohen 1997).

Information disclosure, it has been hypothesized, can work via several mechanisms. Most traditionally, information disclosure programs allow increased transparency that allows market forces to react to differences across firm behavior. Market forces can act due to several motivations. First, investors and shareholders may perceive environmental behavior as an indicator of firm risk management, or more directly as a financial liability (Patten 2002; Konar and Cohen 1997; Hamilton 1995; Khanna et al. 1998; Lyon and Kim 2010). In this scenario, improved information disclosure allows investors and shareholders to more accurately gauge risk and respond accordingly. Firms can be rewarded or punished in the stock market; however,

evidence for this is mixed. Konar and Cohen (1997) and Khanna et al (1998) found that firms with large releases experience decreases of stock prices (Hamilton 1995, 2005; Shapiro 2005), and subsequently reduce emissions (Grant 1997). However, others have found that TRI information was ineffective (Grant and Jones 2004; O'Toole et al. 1997) and that changes in emissions may be due to other regulatory changes (Bui 2005) or largely due to community characteristics (Hamilton 2005; Shapiro 2005). With numerous studies demonstrating a positive link between financial performance and environmental performance, it is possible that good environmental performance may increase investor returns, or that improved financial performance may create enough managerial slack to allow managers to indulge their personal environmental preferences at the expense of shareholders (Lyon and Kim 2010).

Second, improved information disclosure can allow consumers to make choices based on the environmental performance of firms or the environmental labeling of products (Shimshack et al. 2007; Delmas et al. 2010). Firms may gain a marketing advantage through improved environmental performance, or by participating in a voluntary environmental program, including voluntary information disclosure programs. Evidence in this area is also mixed. Information provision can improve product quality (Brouhle and Khanna 2007) and lead to “greener” fuel mixes in the electricity industry (Delmas et al. 2010). However, it has been difficult to distinguish the advantage gained by environmental performance from the advantage gained from environmental marketing, which has been demonstrated to lead to a reputational, financial, and competitive advantage for firms (Prakash 2002; Miles and Covin 2000). In addition, information disclosure may have a negative impact on societal welfare, based on the way information may be interpreted by consumers (Shimshack et al. 2007).

Third, an alternative mechanism, based on the findings of behavioral economics and management research, suggests that the process of collecting improved information can lead

firms to discover improved efficiency and environmental performance. Behavioral economics suggests that the cost of obtaining information is a significant barrier to improved decision-making (Simon 1955). Behavioral economics also asserts that neither producers nor consumers may be utility maximizing due to cognitive barriers in human decision-making processes. One of these barriers, for example, is the default heuristic, which suggests that people continue along the business-as-usual path until a change of course is absolutely essential (Gigerenzer 2004; Gigerenzer and Todd 1999). It is increasingly recognized that firms are boundedly rational actors, and that opportunities for low or no cost environmental improvements may exist (Shadbegian and Gray 2003, 2006). Evidence that investments in capital can improve profitability and environmental outcomes supports this theory (Shadbegian and Gray 2006; Boyd and McClelland 1999), however, critics of this hypothesis argue that it is not plausible that corporate managers systematically overlook profitable opportunities (Palmer et al. 1995) and that what appears profitable ex-post may not have been identified due to high search costs (Jaffe et al. 1995).

Regardless of whether or not low or no-cost environmental improvements exist, considerable variation exists regarding the technological and investment decisions by manufacturers and utilities (Kolk and Pinske 2005). Recent research suggests that individuals and businesses are prone to business as usual behavior – or adherence to the default heuristic, where individuals and firms accept the status quo as a mechanism to make quick and frugal decisions (Gigerenzer and Todd 1999; Bennis et al. 2009; Matisoff 2010). Further, firm managers are frequently faced with short-term goals and priorities that may limit their ability to plan for long-term energy efficiency improvements. These decision-making characteristics may prevent firms from seeking out cost-effective efficiency improvements.

While supplying information to consumers may help firms make better decisions, the process of collecting and supplying information, or forcing managers to think carefully about a process or decision may lead producers to discover improved efficiencies. The process of information disclosure can allow a firm to analyze its activities, seek out means for improvements in efficiency, and improve management techniques; however, the degree to which information disclosure leads to improvements in behavior is related to the level of embeddedness of the information for both the user of the information and the discloser (Weil et al. 2005). If firms and investors are unable to easily access and understand the disclosure of emissions, firm behavior is unlikely to change (Bae et al. 2010).

Significant research has been conducted in the area of information disclosure programs, yet much remains to be learned regarding the design characteristics of information disclosure programs and how these promote or hinder performance (Stephan 2002). In particular, the performance of different designs of information disclosure programs – and the performance of programs mandated by government authority versus those conducted due to voluntary efforts by firms is not well understood. In the next section, I discuss the design of information disclosure programs in the context of voluntary environmental programs.

2.2. Information Disclosure and Voluntary Environmental Programs

Voluntary environmental programs (hereafter called VEP) were developed by industry and government with the aim to reduce confrontation between firms and government in environmental policy, reducing the cost of the implementation of environmental policy while increasing satisfaction by stakeholders (Khanna 2001). VEP include a wide variety of programs including industry led programs, programs led by non-profits, public programs which are led by government and firms are invited to participate, and negotiated agreements between industry and government (Koehler 2007). Motivations for VEP have been similar to the motivations for

information disclosure programs. Firms attempt to improve risk management, deflect more costly mandatory regulation, and gain marketing advantages, while government seeks to implement avoid costly and time-consuming regulatory intervention (Börkley et al. 1998; Alberini and Segerson 2002; Bizer 1999; Grepperud 2002; Koehler 2007; Lyon and Maxwell 2007; Segerson and Miceli 1998; Videras and Alberini 2000; Khanna 2001; Lyon and Maxwell 2003; Morgenstern and Pizer 2007).

There are two ways in which information disclosure programs may be viewed as voluntary programs. First, there are an increasing number of information disclosure programs in which participation is voluntary. Examples include the Department of Energy 1605b program, where firms can choose to disclose carbon emissions and the Carbon Disclosure Project, where firms can choose to disclose carbon emissions to investors. Many product labeling programs also fall into this category. Second, mandatory information disclosure programs may be viewed similarly to voluntary programs in that they do not specifically require behavioral change by the regulatory actors (other than disclosure). While disclosing emissions is mandatory, any reduction in emissions or change in environmental behavior is voluntary.

To date, most research on voluntary environmental programs has sought to analyze whether these programs could replace mandatory policy by examining the effectiveness of these programs. Increasingly, policy researchers have concluded that voluntary policy cannot replace mandatory policy (Lyon and Maxwell 2007; Vidovic and Khanna 2007). While firms that participate in voluntary policy have modestly improved their environmental performance, firms that have not participated have improved their behavior as well, leading researchers to conclude that voluntary programs likely formalize environmental improvements that would have occurred without program intervention. These results have led to a pessimistic outlook on voluntary

environmental programs as a mechanism to improve environmental performance (Lyon and Maxwell 2007).

3. Theory and Contributions of this Research

Recent research has focused heavily on the design of information disclosure programs, in order to attempt to understand what makes information disclosure programs more or less successful. Increasing evidence suggests that the manner in which information is provided to potential users may be the most important factor in determining whether information provision programs can be effective (Bae et al. 2010; Weil et al. 2005; Kolk et al. 2008). If data is made available to stakeholders in user-friendly manner, it may be more consequential than if raw data is simply released to the public. Information that is more detailed, accurate, and congruent to a policy goal may be more effective for achieving a policy outcome (Dranove et al. 2003).

Private voluntary information disclosure programs may have more incentive to cater to the interests of stakeholders than mandatory information disclosure programs. These private voluntary programs, which are run by NGOs or by stakeholder groups have more incentive to ensure that information collected and disseminated is available in an easy to use format. For example, the CDP maintains a searchable database with archived survey responses from all large corporations, while the Department of Energy's 1605b voluntary carbon reporting program participation information and data must be extracted from a series of reports and appendices that have not been updated online since 2005. State program data must be obtained from state energy offices and may not be complete, up to date, or available online. NGOs and other third party organizations can make changes over time to improve the quality, detail, and accuracy of the information collected in order to satisfy stakeholder concerns, and research has demonstrated the potential for information disclosure to be most effective when made accessible to third parties, including states and NGOs for processing and dissemination (Bae et al. 2010). The CDP, for

example, has expanded / reorganized questions each year and worked to improve the quality of information being collected and disseminated; however, the CDP is increasingly restricting access to those who purchase a subscription based service, which may limit the dissemination of the information. In contrast, government information disclosure programs typically pass through legislation or a rule-making process, and may be unlikely to adapt over time to changing demands from stakeholders. While the CDP contains information regarding firm strategy, firm perceptions of risks and opportunities, and firm behavior, state and government programs tend to focus more exclusively on the raw emissions data. Government run information disclosure programs may release data in a raw format, and data releases may be delayed due to budget and time constraints and be less useful to stakeholder groups.

If private voluntary carbon disclosure programs collect more detailed information and disseminate this information more effectively than government-run programs, private programs should be expected to have more of an impact on environmental behavior. Private programs should encourage electricity generators to discover and find inefficiencies to make efficiency improvements, and the disseminated information should be employed by investors and consumers to pressure firms to make environmental improvements.

Hypothesis 1: Electric generators participating in the CDP will reduce carbon intensity more than power plants subject to state carbon reporting requirements.

A second motivation for this research is to understand how different pollutants may be impacted by information disclosure programs. Toxic releases, for example, represent risk due to possible litigation. Because toxics are frequently unpriced in the market, information disclosure offers an opportunity to incorporate the possible future costs of toxic emissions, or gauge the quality of management based on the response to such emissions (Hamilton 1995). Carbon dioxide, however, represents a very different pollutant from toxics. It is generated primarily from

the combustion of fossil fuels, and because fuel is costly, firms already face an incentive to reduce costs to maximize profits (Morgenstern and Pizer 2007).

Another complicating factor, which makes carbon dioxide and electric utilities an interesting case study, is whether or not electric utilities attempt to minimize costs. Electricity markets are highly regulated and electric utilities are frequently able to pass along the costs of fuel and capital investments to consumers. Thus, it remains unclear whether firms will be more or less able to take advantage of possible efficiency gains. On one hand, utilities may be able to pass along any additional costs associated with efficiency gains to consumers; on the other hand, utilities may not have motivation to attempt to realize possible efficiency gains. Overall, I test the assumption that profit-maximizing utilities will not take unilateral action to reduce total carbon dioxide emissions.

Hypothesis 2: Neither the electric generators participating in the state reporting requirements program, nor the CDP will reduce total carbon emissions.

By examining the impact of a voluntary information disclosure program, more can be learned about the different types of voluntary programs and their effectiveness to get a better understanding of policy tools, and how they work in practice. Voluntary environmental programs can encompass many different policy tools and to date, there are few, if any, published empirical evaluations of a voluntary information provision program, and there are few, if any, studies that compare the effectiveness of different information provision programs. Voluntary programs are particularly difficult to assess due to selection bias and the difficulties of obtaining data both pre- and post- intervention, and for participants as well as non-participants. While there are multitudes of studies of individual voluntary programs, it is not clear which types of programs work better than others. Assessing an information provision program can add to the portfolio of

assessments of voluntary programs and help improve understanding of policy design policy tool choice.

4. Research design

In this section I discuss my sample selection and data collection process, including the collection and coding of plant level, firm level, and state level variables. I then discuss my methodology in detail, including the discussion of a propensity score matching model and a difference-in-differences model. Table 1 below shows the specification of each variable included in each model considered.

4.1. Sample Selection and approach

Two information disclosure programs were selected for this research. First, the Carbon Disclosure Project (CDP) is a private voluntary initiative designed to promote improved management of carbon by pressuring firms to report their carbon emissions, and describe their carbon strategies and carbon related risks and opportunities. The CDP began in 2000 with a London-based coordinating secretariat for institutional investors to gain insight to climate related risk of Fortune 500 publicly traded corporations by standardizing reporting procedures for climate change related activities. The results of the first cycle of the project, released February 17th, 2003, were endorsed by approximately 35 investors controlling \$4.5 trillion in assets. By the end of 2007, the CDP had grown considerably and was funded and run by over 385 institutional investors including major players such as Goldman Sachs, Merrill Lynch, and state pension funds, controlling over \$40 trillion in assets. By 2007, over 2,400 firms were targeted and 1,300 firms responded to the survey (CDP4) reporting on various aspects of carbon management (Kolk et al. 2008). Of the Fortune Global 500 companies, CDP4 resulted in a 91% response rate and 72% answered the questionnaire in full. The CDP ranks firms based on the

quality of their responses and rewards transparent firms with acknowledgement in their Carbon Disclosure Leadership Index. Firms are allowed to make their responses public, or can keep responses limited to the institutional investors that fund the program.

Second, state reporting programs are mandatory state efforts designed to help states manage and prepare for mandatory carbon regulation. Legislation enacting emissions reporting of greenhouse gases had been passed in eighteen states by 2008. By 2007, state reporting mandates were in effect in Wisconsin, New Jersey, Connecticut, West Virginia, and Maine.¹ Wisconsin, the first state to require emissions reporting, required reporting since 1993 for firms that emit more than 100,000 tons of carbon per year. The state's strong community right-to-know ethic makes the information readily available to the public via the Internet. New Jersey's mandatory reporting requirement began in 2003, focusing on CO₂ and methane, with a capacity threshold of 25,000 tons of CO₂ equivalent, determined by criteria air pollutant emissions. West Virginia, in 2007, began requiring reporting for firms that already had reporting requirements for other air pollutants.

In order to measure the effectiveness of the two information disclosure programs, I chose to focus on power plant emissions and calculate estimated CO₂ emissions by the type and amount of fuel use. There are a variety of practical reasons for limiting the sample to power plants and calculating estimated CO₂ emissions in this manner. First, power plants are the largest generators of CO₂ and are the most likely targets of any efforts to control greenhouse gas emissions. Second, emissions data from specific programs varies greatly in the method of accounting used and the accuracy and quality of the data (Lyon and Kim 2011). Third, data sources such as EPA's Continuous Emissions Monitoring System are incomplete and have

¹ While state reporting requirements had been passed by many states, there is generally a delay between the passage of the legislation and the implementation of the reporting requirements.

produced highly variable and potentially inaccurate estimates of CO₂ emissions (Lyon and Kim 2011). Fourth, emissions data for manufacturing plants and firms not participating in voluntary or mandatory information disclosure programs is not publicly available, making it impossible to establish a control group. And finally, emissions monitoring in the states, in Europe, and in future U.S. federal regulation is likely to be based on engineering based estimates, derived from fuel use data, making this approach consistent with state, national, and international standards, as well as other approaches in the literature (Morgenstern et al. 2007; Lyon and Kim 2011).

4.1.1. Data collection

Three types of data had to be collected to analyze the effectiveness of these programs. First, plant level data, including CO₂ emissions and non-fuel expenditures were collected as the dependent variables. Electricity generation and plant construction year were also collected at the plant level. Second, because participation in voluntary programs is determined at the firm level, firm level data were collected, including firm size (measured as revenue) and whether or not a firm is publicly traded. Finally, state characteristics relating to the regulatory climate of each state were coded and collected to control for varying levels of regulations and incentives that might impact regionally situated electricity producers. Table 1 below lists the variables that were collected and whether they were included in the propensity score matching model, or the difference-in-differences model (or both).

Plant level data

Fuel use data was used to estimate carbon emissions. To calculate carbon dioxide emissions, the amount of each type of fuel used in each power plant was multiplied by the heat rate, and the DOE regulations were used for the 1605b voluntary program in order to determine carbon dioxide emissions for each power plant reporting fuel use to the Energy Information

Administration.² Plant level data were collected from 1994 – 2007 for approximately 5,000 prime movers³ (engines or turbines), which was then compiled to generate fuel use data for approximately 1,000 power plants in the United States, totaling 14,393 plant-year observations. Plant level data were compiled with the assistance of Indianapolis Power and Light from the Velocity data suite, which relies primarily on data collected from EIA forms 861, 412, 906, 920, 923, and FERC form 1.⁴ In addition, variables were collected for the purposes of calculating additional dependent variables and in order to control for plant characteristics. These variables include plant capacity, electricity generation, year of construction, and non-fuel operating expenditures.⁵

Firm level data

Firms were coded as public or private using Compustat, Google Finance, and other search engine methods. Firm revenue data were collected from the Compustat database.⁶

² Because the 1605b regulations only have carbon dioxide emissions multipliers for major types of fuel, I used the closest match for rare types of fuel.

³ Prime movers are the engines or turbines in a power plant. Each power plant may be composed of multiple prime movers. Fuel use is reported to the EIA at the prime mover level.

⁴ Because fuel use data, data containing plant characteristics, and firm level and state level data were contained in separate datasets, data were merged into one large dataset using plant ID numbers, and operator ID numbers.

⁵ Missing firm construction year data and capacity data were periodically encountered. In these cases data was carried down from previous years.

⁶ Following Berry and Fording (1997), I imputed missing data for firms missing a year to several years of data using Stata's linear trending missing data function (Berry and Fording 1997). These observations were less than 5% of the total observations.

State level data

State regulatory data and information regarding renewable energy and energy efficiency programs were compiled from the Database for State Incentives for Renewable Energy (DSIRE) and individual state energy offices, as well as the Environmental Protection Agency website (DSIRE 2009). The changing regulatory environment in each state may have a relationship with the electricity generation decisions made by individual power plants. Previous research has demonstrated the number of energy programs active in a state to be the product of political ideology, geographic resources, economic resources, and carbon-intensive industry present in a state (Matisoff 2008). Similarly to Hall and Kerr (1991) and Gray and Shadbegian (2003), who employ a count of laws regulating toxic waste in the states in order to construct a TOXIC index, measuring the regulatory stringency of each state, I count the total number of renewable energy and energy efficiency programs active in a particular state, for each year, as an indicator of regulatory activity in each state (Gray and Shadbegian 2003; Hall and Kerr 1991). This was compiled through the DSIRE website, as well as via e-mails and phone calls to individual state energy offices. While this measurement is an imperfect measurement of the regulatory stringency of each state, it is a good time-variant indicator of the changing energy regulatory environment at the state level, and the count of programs is highly correlated with state ideology, geographic resources, and other political and economic factors (Matisoff 2008).⁷ The EPA website and state energy offices were used to determine whether or not states had active restructuring in each year.

⁷ For more information about the types of energy policies included in this measure, see the DSIRE database and Matisoff (2008). For more information about the reliability of this measurement, see Matisoff (2008).

Obstacles and Challenges

Due to the nature of this work, a variety of tradeoffs had to be made to secure such a complete and detailed dataset. First, plant data is only available for power plants that have greater than 25 megawatt capacity. Second, unregulated electricity generators did not have to report plant data beginning in 2003. I was able to determine which plants had closed after 2002, and which had ceased to report data based on whether the plant had reported fuel use, which was still required after 2002. Third, plants that do not have reported fuel use do not appear in this dataset, eliminating many renewable energy plants. Fourth, deregulated plants that began operation in 2003 or later may not have appeared in the dataset, due to changes in reporting requirements. Finally, nuclear plants, hydro plants and plants operated by universities were also eliminated from the dataset to achieve greater unit homogeneity. By focusing on this subset, I exclude shifts in power generation away from fossil fuels and into renewables and nuclear power, but am able to capture with great precision, the changes occurring at the power plant level, including changes in fuel use, demand reduction, and improved efficiency. Altogether, the dataset totals 13,552 plant-year observations, or 968 power plants over 14 years.

<insert table 1 about here>

4.2. Methodology and Identification Strategy

This study employs propensity score matching, to control for static observable differences between the treatment group and control group, and a difference-in-differences model to control for unobservable static differences between the treatment group and the control group. I test for robustness by estimating effects with a fixed effects model as well. These results are included in the appendix. Below, I review the literature and methodology in further detail.

Non-experimental methods of assessing program effectiveness are susceptible to a variety of biases (LaLonde 1986). These include selection biases based on the propensity to join a

program, the distributions of propensity to join a program, and “pure” self-selection, when individuals’ self selection behavior is based on information that researchers cannot observe, or is caused by inter-temporal dependence of an outcome variable (Jung and Pirog 2010; Heckman et al. 1997; Heckman et al. 1999). Selection bias based on the observable propensity to join a program can be controlled for using propensity score matching (Heckman et al. 1997; Jung and Pirog 2010; Dehejia and Wahba 2002). “Pure” selection bias can be decomposed into three sources of bias, which have various implications. First, individuals with higher returns from the program may be more likely to participate. Second, individuals with lower opportunity costs to join might be more likely to participate. The third source occurs when low opportunity costs of joining are correlated with program outcomes (Jung and Pirog 2010). Of these sources of pure selection bias, the second and third sources tend to underestimate treatment effects, while the first source overestimates treatment effects (Jung and Pirog 2010). The second source of pure selection bias can be controlled for using a difference-in-differences approach, and overall, fixed effects estimators and difference-in-difference estimators perform well in reducing bias, and in particular, the effect of treatment on the treated (TT) (Jung and Pirog 2010).

Following Heckman et al., (1997), and similarly to Lyon et al., (2011) this study employs propensity score matching and a difference in differences approach, which has been demonstrated effective at reducing bias, especially when it is due to temporally invariant omitted variables – that is, static differences between the treatment group and control group (Heckman et al. 1997). It is an extremely effective way of measuring the average treatment effect on the treated under much weaker assumptions than matching alone (Heckman et al. 1997). The effects of the treatment on the treated can be identified under the relatively weak mean conditional independence assumption, formulated in terms of $P(X)$, where X represents the observable

conditions that lead to program participation and D represents whether or not plants participate in a specific program.

$$E(Y_0 | P(X), D = 1) = E(Y_0 | P(X), D = 0) \quad (1)$$

In order to fulfill this assumption and identify the causal effects in the difference-in-differences approach, at least one of the matching variables (X) must be uncorrelated with the outcome variable Y (in this case, the annual change in plant-level carbon dioxide emissions) (Caliendo and Kopeinig 2008). For more information on this identification strategy, or alternative identification strategies, see Heckman et al. (1997), or Heckman and Robb (1986). A more thorough discussion of the consequences of this approach follows below.

4.2.1. Matching

Because plants participating in a voluntary program may be systematically different than plants not participating in a voluntary program, it is necessary to establish a control group of plants for each of the treatment groups. Creating a matched control group can serve as a method to form a quasi-experimental contrast between a treatment and control and provide reliable estimates of program effectiveness, even when the treatment and control groups are highly dissimilar (Morgan and Winship 2007; Dehejia and Wahba 2002). Because of the large size of the dataset, and multiple time period nature of the dataset, I chose to use a nearest-neighbor propensity score matching method, which has been demonstrated to effectively reduce selection bias (Heckman et al. 1996; Dehejia and Wahba 2002). Using this method, I match plants based on the probability that plants are participants in each voluntary program, given plant, firm, and state characteristics. Following Morgenstern et al (2007), participating plants are then matched, without replacement, to the non-participating plant that has the closest probability of joining the voluntary program.

$$Pr[joining = 1 | \sum x] = \frac{\exp(a + b_1x_1 + b_2x_2 + b_ux_u)}{1 + \exp(a + b_1x_1 + b_2x_2 + b_ux_u)} \quad (2)$$

Plants from the CDP were matched with a sample of non-participating plants, and plants participating in mandatory state reporting programs were matched based on participation status in 2007. A one to one nearest neighbor match was conducted using the Stata user generated program `psmatch2`, using a logit regression (Leuven and Sianesi 2003). For each program, plants were matched by `psmatch2` using the likelihood of participation in each voluntary program, based on whether or not the firm is publicly traded (1 = yes), the year of plant construction, the capacity of the plant (in megawatts), the number of state energy programs active, the parent company size (measured as the natural log of millions of dollars in revenue), and whether or not utility restructuring was active in a state (1=yes).

In order to fully identify the causal effects in the difference-in-differences approach below, it is important to have at least one predictor in the propensity score matching equation that is correlated with the decision to participate, but is uncorrelated with plant level carbon dioxide emissions. The *parent* company size (revenue) ought to be uncorrelated with *plant* level annual change of carbon dioxide emissions. Because each holding company owns multiple plants – and in many cases operates in multiple industries – there is little reason to believe that the size of the corporate parent is correlated with plant-year observations of changes in carbon dioxide emissions. However, the size of the corporate parent is one of the strongest predictors of whether or not a firm joins a voluntary environmental program, making it a good instrumental variable for this purpose.

For the CDP, participation decisions in voluntary environmental agreements are made by corporate parents, rather than individual plants. For the state reporting programs, participation depends solely upon location, but the matching method helps find plants that are good comparisons. Investor owned utilities are much more likely to participate in voluntary environmental agreements because the CDP specifically targets large, publicly traded firms. Finally, because of varied state regulatory activity, plants that operate in states with more regulatory activity related to energy may be more likely to participate in voluntary initiatives.

Unmatched participating or non-participating plants were discarded from the sample, leaving 5,180 plant-year observations for the CDP and 2,352 plant-year observations for the state reporting requirements. While matched samples allow me to assume that there is no difference between the treatment group and the control group, given the observables included in the model, it is still possible that unobserved differences within the treatment group and control group exist (Morgan and Winship 2007; Moffit 1991).

Once matching has been completed, the expected outcomes for each the control group, and the treatment group are the same, given the observable differences in the treatment group and control group. I test this assumption using a Hotellings T-squared test statistic on the joint equivalence of the covariates between the treatment and control groups (Caliendo and Kopeinig 2008). However, this method does not control for unobserved heterogeneity across plants, nor does it control for changes in conditions over time. These issues will be addressed in the difference-in-differences approach discussed next.

4.2.2. Difference in differences approach

In order to control for the unobserved heterogeneity or omitted variables in matching process as well as changes in conditions at each plant, I take the first difference of the outcome variable y and each of my control variables λ over time period s , where x is not differenced and

is a dummy variable that denotes program participation in year t (Moffit 1991; Allison 1990; Morgenstern et al. 2007). Thus, I estimate the change in the dependent variable as a function of program participation and changes in conditions.

$$\Delta_s y_{it} = \alpha + \sum \beta_{it} X_{it} + \sum \theta_{it} \Delta_s \lambda_{it} + e_{it} \quad (3)$$

where: $\Delta y_{it} = y_{it} - y_{i(t-1)}$ and $\Delta \lambda_{it} = \lambda_{it} - \lambda_{i(t-1)}$

This equation is estimated using ordinary least squares, with robust standard errors clustered on the panel variable i .

The difference in differences approach controls for any static heterogeneity between the treatment group and the control group, assuming that participants and controls have the same distributions of unobserved attributes; that they have the same distributions of the observed attributes; and that they are in a common economic environment (Heckman et al. 1997). The time-variant control variables control for any observable conditions that change over time including changes in the state regulatory environment (measured as the number of energy programs in a state each year, and whether or not a state has active electricity restructuring), firm growth rate, and changes in plant-level electricity generation. Thus, the difference in differences approach does not control for any time-variant unobserved heterogeneity, such as a change in firm philosophy over time, or a change in firm management over time, and assumes constant program effects over time (or alternatively calculates an average treatment effect on the treated over time).

The matching method is used separately for the Carbon Disclosure Project and the state reporting requirements. Each matched sample is used to evaluate each program. The difference-in-difference method is repeated for each program for plant level CO₂ emissions (in metric tons), and plant level total non-fuel costs (in dollars).

5. Results

<<insert table 2 about here>>

As demonstrated above in table 2, firm, state, and plant characteristics provide a fair amount of explanatory power to help predict which plants participate in state reporting requirements or the Carbon Disclosure Project, allowing a matched sample to be created for each program. While parameter estimates are unbiased and consistent, the standard errors are incorrect due to correlation across observations on the independent variables. This heteroskedasticity means that the parameter estimates cannot be used for hypothesis testing on the independent variables, but can be used for predictive purposes. However, these results seem to support previous findings demonstrating that larger, publicly traded firms, and plants located in areas with stronger regulatory regimes are more likely to participate in voluntary policy. Plants participating in state reporting requirements seem to belong to smaller publicly traded firms in areas with stronger regulatory regimes. After eliminating unmatched observations, and calculating the first difference of observations, two matched samples are left totaling 2,184 plant-year observations for the state reporting programs, and 4,810 plant-year observations for the Carbon Disclosure Project (see table 3 below).

Recent literature suggests that because poorly matched samples may create bias in estimated program effects, the matched samples should be tested for balancing to reduce bias and ensure that the matching process sufficiently controls for observable differences between the treatment and control group (Smith and Zhang 2009; Smith and Todd 2005a, 2005b). A variety of tests exist to check for balancing, and these methods have received criticism due to the inconsistency of results (Lee 2006; Smith and Zhang 2009), and whether or not balancing tests are even necessary (Dehejia 2005).

While a balancing test may not be essential for this sample, because the difference in differences model will control additional heterogeneity by examining only the within unit changes over time, following Smith and Petra, (2005b), I conduct a Hotelling T-Square balancing test to demonstrate the similarity of treatment group and control group after matching. The Hotelling T-Square test is an F-test on the joint equivalence of the covariate means of the treatment group and control group and can be conducted in Stata. As Table 3 below demonstrates, the treatment group and control group have extremely similar means and standard deviations, and the F test fails to reject the null hypothesis that the means of the two samples are jointly equivalent. Both the CCX sample and the CDP sample appear balanced by both measures, even before within differencing. These results also demonstrate that the matching process increased the similarity of the treatment and control samples, at least across observables.

<<insert Table 3 about here>>

<<insert Table 4 about here>>

Results from the differences-in-differences model (see table 5 below) demonstrate evidence of emissions intensity reductions due to participation in the Carbon Disclosure Project. When controlling for electricity generation, participation in the Carbon Disclosure Project is associated with a reduction of plant-level emissions by 27,440 metric tons, per plant, during the period of participation, in contrast to what would have occurred without CDP participation. Reductions without controlling for electricity generation are not statistically significant. Average plant emissions are about 2.34 million tons per year. Because plants average 2.69 years of participation, average emissions reduction per plant is about ten thousand metric tons, per year, when controlling for electricity generation. *Thus, participating plants in the CDP reduce emissions by about 0.4% per year, for 2.7 years, when controlling for electricity generation.*

While absolute CO₂ reductions are not statistically significantly different from 0 at reasonable values of α , when controlling for electricity production, the reduction of carbon dioxide emissions gasses is statistically significant with p value of .01. Thus, it appears that program participation in the CDP causes firms to pay more close attention to carbon intensity rather than absolute carbon emissions, consistent with the hypotheses above. In order to test for robustness, I also perform a fixed effects estimation of the model. Results from the fixed effects model are included in the appendix. The fixed effects model estimates a greater magnitude of reductions of CO₂ when controlling for electricity generation, but estimates an increase in total CO₂ emissions. Standard errors are larger in the fixed effects model, likely because the fixed effects model also measures between variation, rather than simply measuring within variation.

State reporting requirements, in contrast, do not seem to impact greenhouse gas emissions or intensity, regardless of model specification. Participating plants in the sample have averaged 6.5 years of program participation. Parameter estimates suggest that the total program effect led to an increase of 2.4 thousand metric tons, when controlling for electricity generation, and 5.7 thousand metric tons of additional total carbon emissions over the course of program participation. These results are neither substantively nor statistically significant. Results from a fixed effects estimation are included in the appendix, and show similarly insignificant results.

<<insert Table 5 about here>>

6. Discussion

This model assumes that electric utilities can improve the efficiency of existing plants through upgrades and improved maintenance or that utilities can replace older fossil fuel plants with newer more efficient power plants, or by switching fuel from high carbon to low carbon fuel. Several limitations of the data exist. Renewable energy production such as wind, solar, geothermal, and hydro-electric production are not captured by this dataset. In addition,

improvements in nuclear efficiency are ignored by this data. These limitations suggest that improvements by participating firms may understate the total program impact of the CDP.

These results demonstrate that the decision to participate in the Carbon Disclosure Project appears to be correlated with shifts in carbon dioxide intensity. In contrast, participation in state disclosure programs does not have a similar impact. Neither program results in reductions of total carbon emissions. These results confirm the expectations laid out in the hypotheses.

Because firms already account for fuel costs in production decisions, and because there are no limits in information disclosure programs, no absolute reductions in carbon dioxide emissions were anticipated, and none were observed. However, the Carbon Disclosure Project appears to lead firms to improve the management of carbon dioxide emissions, either by allowing participating firms to improve management more easily by leading them to collect more useful information, by creating outside pressure on firms to improve carbon management, or, perhaps simply creating a reporting mechanism that rewards firms that have quietly taken measures to improve carbon management. Despite controlling for observable and unobservable static heterogeneity across power plants, and despite controlling for observable changes over time across powerplants, statistical techniques do not allow researchers to discount the possibility that unobservable changes in firm management are correlated with the decision to begin reporting to the CDP which leads to both firm participation and improvements in carbon intensity.

Program participation in the CDP is measured as a dummy variable, which captures the observable change in behavior caused by program participation, but also any unobservable changes in firm behavior that directly coincide with the decision to participate. It seems likely that the decision to participate in the CDP is closely related to a firm's decision to take steps to improve carbon management.

In contrast, mandatory state reporting programs do not seem to have any impact on carbon dioxide emissions or intensity. The parameter estimates, which indicate a slight increase of carbon dioxide emissions and intensity, are statistically and substantively indistinguishable from zero.

These results point to the importance in considering the design of information disclosure programs. The CDP and state disclosure programs are vastly different. The CDP requires detailed information regarding firm management strategies while state disclosure only requires basic raw information. The CDP contains a centralized, subscription-based database with searchable reports, and has worked to modify data and improve questions over time. In contrast, state programs are a hodgepodge of data reporting requirements which may not be easily accessible and may not be updated. These results emphasize the unobserved management decision and process involved in collecting carbon dioxide information that leads to improved performance amongst CDP participants. If firms simply have to report carbon dioxide emissions to authorities – which is as simple as plugging fuel data into an equation – there is little impact on firm carbon management. In contrast, if a firm makes the decision to increase focus on carbon management and improve environmental management strategy, and reports on this strategy to its shareholders – a firm is much more likely to improve carbon performance.

These findings support other recent findings in the information disclosure literature. Recent research has also found the DOE 1605b program to be similarly ineffective (Lyon and Kim 2011). This program also does a poor job disseminating results – where participation and data are contained in appendices of annual reports, and as of January 2011, have not been updated more recently than 2004. Overall, these results point to the importance of designing information disclosure programs that are transparent, that adapt information collection efforts to more effectively convey relevant and important information to stakeholders, and that disseminate

those results to stakeholders. These results bolster findings by Bae et al (2010) who found that the manner in which information disclosure data are disseminated matters greatly.

Even if results of this study do not reflect changes caused by the CDP, but rather, changes reflected by participation in the CDP (that firms who improve behavior choose to also participate in the CDP), CDP participation, then, resembles a manner in which firms can effectively disseminate information regarding their environmental performance to shareholders. Because this is a private effort, rather than a public one – no public support is used to subsidize or endorse CDP efforts.

7. Conclusions and directions for future research

On one hand, this research shows the potential for information disclosure programs to play an important role in improving plant level environmental management. It also highlights the importance of not just collecting data from firms, but that the dissemination efforts and types of information collected are highly important as well. While the CDP is a private, voluntary, program run by investors, it may hold important lessons for the design of future information disclosure programs.

On the other hand, this research also highlights the limitations of information disclosure. The state reporting requirements had no impact on either carbon intensity or total carbon emissions. The CDP also had no impact on total carbon reductions. While information disclosure programs, product labeling, and improving transparency have been hailed as market-friendly ways to improve environmental behavior without imposing costly regulations, it seems unlikely that lessons from toxics can be applied to carbon. While toxic emissions are an unpriced liability risk, carbon emissions do not share these similar traits, and carbon emissions are directly linked to electricity output. If carbon dioxide emissions are to be reduced, it will likely require stronger regulation than disclosure alone or recognition for transparency.

The effectiveness of the Carbon Disclosure Project in comparison to state mandatory reporting requirements suggests that program participation is associated with improvements in a firm's carbon management. While participation is measured with a binary variable, future research should seek to parse the quality of CDP responses and the information contained within CDP responses to determine whether the quality of the data collection matters, or simply whether participation matters. If the CDP truly is leading firms to improve carbon management, either through outside pressure or internal improvements, firms that are more transparent should improve carbon management more than firms that are less transparent, and firms that report significant improvements in carbon management should experience greater reductions of carbon intensity.

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Table 1. List of variables used in Propensity Score Matching, Difference-in-differences models, and fixed effects models

| Variables | Level of observation | Included in propensity-score-matching? | Included in difference-in-differences? | Included in fixed effects? |
|---|----------------------|--|--|----------------------------|
| Number of active energy programs | State | X | X | X |
| Δ Number of active energy programs | State | | X | |
| Is energy restructuring active? | State | X | X | X |
| Is firm publicly traded | Firm | X | X | X |
| Firm revenue | Firm | X | | X |
| Δ Firm revenue | Firm | | X | |
| CO2 emissions | Plant | | | X |
| Δ CO2 emissions | Plant | | X | |
| Year of plant construction | Plant | X | | |
| Plant capacity | Plant | X | | |
| Δ non-fuel operating expenditures | Plant | | X | |
| Δ megawatt hours of electricity generation | Plant | | X | |
| Megawatt hours of electricity generation | Plant | | | X |

Table 2: Generating a Matched Sample for the Carbon Disclosure Project: predicting participation in the Carbon Disclosure Project, or state reporting requirements in 2007

| Logistic Model | State Reporting Requirements | CDP |
|---------------------------------------|------------------------------|-------------------|
| Number of Observations | 966 | 700 [†] |
| LR Chi ² | 59.37*** | 101.83*** |
| Pseudo R ² | .104 | .1259 |
| Publicly Traded Firm (1=yes) | 2.11 (.492)*** | † |
| Holding Company Revenue (ln\$000,000) | -.364 (.105)*** | .821 (.099)*** |
| Plant Capacity (MW) | -.00008 (.0002) | .00002 (.00013) |
| Year of Construction | -.004 (.005) | -.0135 (.0045)*** |
| Active State Restructuring (1=yes) | -.264 (.277) | -.240 (.2197) |
| Total State Energy Programs (#) | .073 (.014)*** | .03387 (.0133)*** |
| Constant | 6.52 (10.24) | 19.88 (8.81)** |

* represents significance at the $\alpha = .10$ level

** represents significance at the $\alpha = .05$ level

*** represents significance at the $\alpha = .01$ level

† because only publicly traded companies participated in the CDP, the matching software excludes non-publicly traded companies from the sample

Table 3: Means and Standard Deviations of Matched Samples, before and after matching, with Hotelling T-Square Balancing Test

State Reporting Requirements Matched Sample (84 pairs)

| Variable | Control Mean (pre) | Control Stdev (pre) | Control Mean (post) | Control Standard Deviation (post) | Treatment Mean (pre) | Treatment Stdev (pre) | Treatment Mean (post) | Treatment Standard Deviation (post) |
|------------------------------------|--------------------|---------------------|---------------------|-----------------------------------|----------------------|-----------------------|-----------------------|-------------------------------------|
| Publicly Traded Firm (1=yes) | .695 | .461 | .90 | .295 | .843 | .366 | .87 | .339 |
| Firm Level Revenue (ln\$000,000) | 7.99 | 1.83 | 7.93 | 1.64 | 8.14 | 1.59 | 8.06 | 1.65 |
| Plant Capacity (MW) | 640.13 | 671.05 | 686 | 720.31 | 535.44 | 576.42 | 562 | 608.15 |
| Year of Construction | 1968 | 21.59 | 1961 | 22.85 | 1964 | 23.67 | 1964 | 20.64 |
| Active State Restructuring (1=yes) | .403 | .491 | .44 | .499 | .506 | .503 | .51 | .502 |
| Total State Energy Programs (#) | 14.49 | 8.36 | 18.83 | 9.17 | 20.56 | 8.29 | 20.64 | 8.27 |

Two Group Hotelling T-Square = 7.77

F Statistic = 1.26; p-value = .281

Carbon Disclosure Project Matched Sample (185 pairs)

| Variable | Control Mean (pre-matching) | Control Stdev (pre-matching) | Control Mean (post) | Control Standard Deviation (post) | Treatment Mean (Pre) | Treatment Stdev (Pre) | Treatment Mean (post) | Treatment Standard Deviation (post) |
|------------------------------------|-----------------------------|------------------------------|---------------------|-----------------------------------|----------------------|-----------------------|-----------------------|-------------------------------------|
| Firm Level Revenue (ln\$000,000) | 6.81 | 1.88 | 8.33 | 1.38 | 9.06 | .819 | 8.51 | .89 |
| Plant Capacity (MW) | 489.73 | 529.87 | 693 | 639.78 | 759.46 | 742.39 | 741 | 677.82 |
| Year of Construction | 1971 | 22.13 | 1971 | 20.89 | 1964 | 21 | 1976 | 20.70 |
| Active State Restructuring (1=yes) | .35 | .479 | .41 | .492 | .458 | .498 | .36 | .481 |
| Total State Energy Programs (#) | 14.15 | 8.13 | 14.42 | 8.45 | 15.76 | 8.83 | 13.37 | 6.30 |

Two Group Hotelling T-Square = 8.50

F Statistic = 1.683; p-value = .1378

Table 4: Observations in Dataset and for CDP and state reporting programs

| Program | State Reporting Programs | CDP |
|---|--------------------------|--------|
| Number of initial plants | 966 | 966 |
| Initial plant-year observations | 13,558 | 13,558 |
| Matched pairs | 84 | 185 |
| Total plant-year observations after first differencing | 2,352 | 4,810 |

Table 5: State Reporting Mandates versus the Carbon Disclosure Project: Difference in differences model, Effect of Participation on ΔCO_2 Emissions (metric tons), OLS Parameter Estimates Shown, Clustered Standard Errors in Parentheses, on Matched Samples

| Model | State Reporting Mandates1 | State Reporting Mandates2 | CDP1 | CDP2 |
|--|---------------------------|---------------------------|-----------------------|------------------------|
| Observations | 2,184 | 2,184 | 4,810 | 4,810 |
| F Statistic | 2.34** | 7.90*** | 3.54*** | 75.44*** |
| R-Squared | .0028 | .5207 | .0029 | .6017 |
| Program Participation – State Reporting Mandates | 5,762 (18,037) | 2,464 (9,991) | | |
| Program Participation – CDP | | | -17,717 (18,399) | -27,440*** (10,034) |
| State Restructuring | 9,031 (25,926) | 3,676 (12,515) | -1,528 (16,511) | 4,284 (9,607) |
| Δ Firm Revenue (ln \$000,000) | -30,484 (54,381) | -12,280 (15,124) | 18,540 (26,116) | -15,219 (15,484) |
| Total state energy programs | -2,314* (1,231) | -1,147* (656) | 874 (934) | 1,182* (717) |
| Δ State Programs | -6,617** (3,345) | -4,072 (2,563) | -18,985*** (5,035) | -6,810** (3,350) |
| Δ MWh | | .572*** (.136) | | .7410*** (.0354) |
| Constant | 39,797* (23,891) | 13,040 (11,776) | 26,271*** (9,726) | -5,181 (6,930) |

* represents significance at the $\alpha = .1$ level

** represents significance at the $\alpha = .05$ level

*** represents significance at the $\alpha = .01$ level

Appendix 1: State Reporting Mandates versus the Carbon Disclosure Project: Fixed

Effects Model, Effect of Participation on CO₂ Emissions (metric tons)

| Model | State Reporting Mandates1 | State Reporting Mandates2 | CDP1 | CDP2 |
|--|---------------------------|---------------------------|---------------------------|------------------------|
| Observations | 2,352 | 2,352 | 5,179 | 5,179 |
| F Statistic | 1.31 | 315.55*** | 17.05*** | 1,239*** |
| R-Squared | .0193 | .8670 | .0105 | .9538 |
| Program Participation – State Reporting Mandates | 24,708 (61,756) | -6,943 (47,106) | | |
| Program Participation – CDP | | | 60,506* (34,313) | -38,104* (22,875) |
| State Restructuring | 35,688 (44,505) | -17,870 (33,970) | 3,717 (31,141) | 68,459*** (20,745) |
| Firm Revenue (In \$000,000) | 38,859* (23,489) | 37,955** (17,915) | 98,346*** (14,033) | 31,044*** (9,381) |
| Total state energy programs | -1,094 (2,662) | -3,804* (2,031) | 177 (2,558) | -2,250 (1,703) |
| MWh | | .4775*** (.0121) | | .6591*** (.0085) |
| Constant | 1,776,843*** (172,038) | 700,914*** (133,992) | 1,534,300*** (109,218) | 399,768*** (74,150) |

* represents significance at the $\alpha = .1$ level

** represents significance at the $\alpha = .05$ level

*** represents significance at the $\alpha = .01$ level